Aim: To study the Depth Estimation

Objective: To Capturing Frames form a depth camera creating a mask from a disparity map Masking a copy operation Depth estimation with normal camera

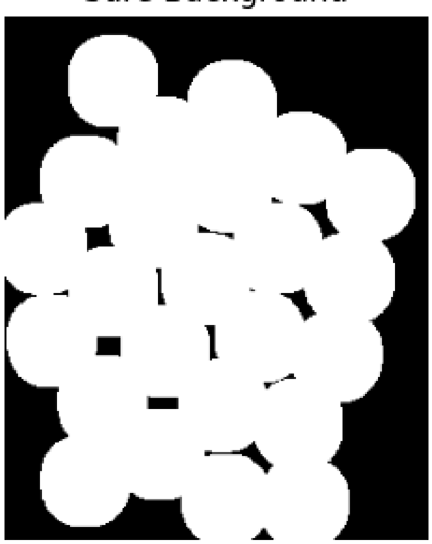
Theory:

The watershed algorithm uses topographic information to divide an image into multiple segments or regions.
The algorithm views an image as a topographic surface, each pixel representing a different height.
The watershed algorithm uses this information to identify catchment basins, similar to how water would collect in valleys in a real topographic map.
The watershed algorithm identifies the local minima, or the lowest points, in the image.
These points are then marked as markers.
The algorithm then floods the image with different colors, starting from these marked markers.
As the color spreads, it fills up the catchment basins until it reaches the boundaries of the objects or regions in the image.

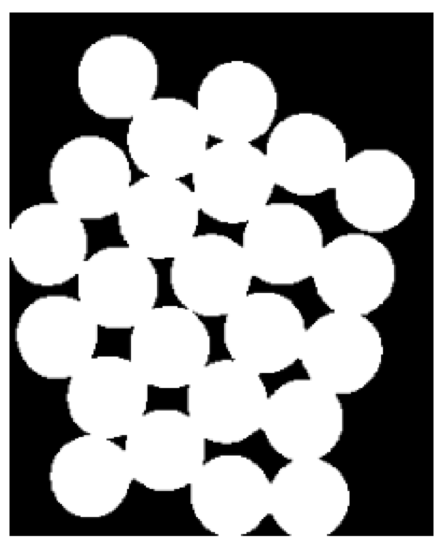
The catchment basin in the watershed algorithm refers to a region in the image that is filled by the spreading color starting from a marker
. The catchment basin is defined by the boundaries of the object or region in the image and the local minima in the intensity values of the pixels.
The algorithm uses the catchment basins to divide the image into separate regions and then identifies the boundaries between the basins to create a segmentation of the image for object recognition, image analysis, and feature extraction tasks.

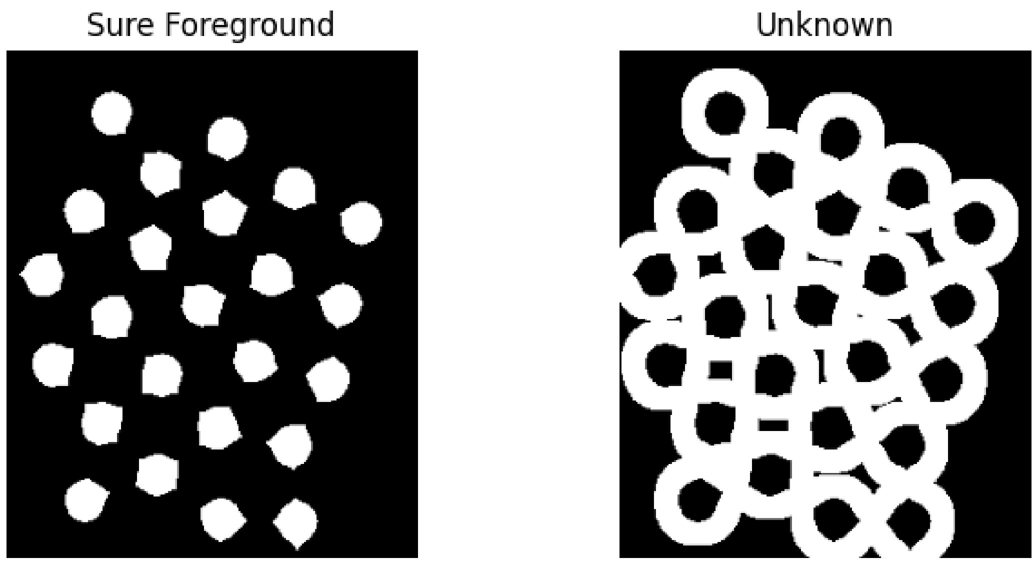
The whole process of the watershed algorithm can be summarized in the following steps:
Marker placement: The first step is to place markers on the local minima, or the lowest points, in the image. These markers serve as the starting points for the flooding process.
Flooding: The algorithm then floods the image with different colors, starting from the markers. As the color spreads, it fills up the catchment basins until it reaches the boundaries of the objects or regions in the image.
Catchment basin formation: As the color spreads, the catchment basins are gradually filled, creating a segmentation of the image. The resulting segments or regions are assigned unique colors, which can then be used to identify different objects or features in the image.
Boundary identification: The watershed algorithm uses the boundaries between the different colored regions to identify the objects or regions in the image. The resulting segmentation can be used for object recognition, image analysis, and feature extraction tasks.

Sure Background



Distance Transform




Sure Foreground
Unknown


Input
GrabCut Mask
Output

Code:

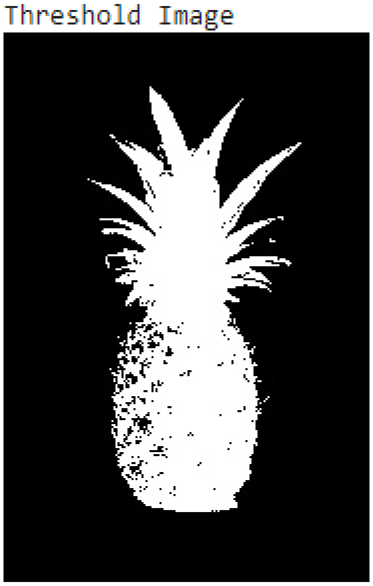
```
import cv2

import numpy as np

from IPython.display import Image, display

from matplotlib import pyplot as plt


# Plot the image

def imshow(img, ax=None):

  if ax is None:

    ret, encoded = cv2.imencode(".jpg", img)

    display(Image(encoded))

  else:

    ax.imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))

    ax.axis('off')


#Image loading

img = cv2.imread("fruits.jpg")


#image grayscale conversion

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Show image

imshow(img)


#Threshold Processing
```

```
ret, bin_img = cv2.threshold(gray,
              0, 255,
              cv2.THRESH_BINARY_INV + cv2.THRESH_OTSU)
print("Threshold Image")
imshow(bin_img)

# noise removal
kernel = cv2.getStructuringElement(cv2.MORPH_RECT, (3, 3))
bin_img = cv2.morphologyEx(bin_img,
            cv2.MORPH_OPEN,
            kernel,
            iterations=2)
print("noise removal")
imshow(bin_img)

# Create subplots with 1 row and 2 columns
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(8, 8))
# sure background area
sure_bg = cv2.dilate(bin_img, kernel, iterations=3)
imshow(sure_bg, axes[0,0])
axes[0, 0].set_title('Sure Background')

# Distance transform
dist = cv2.distanceTransform(bin_img, cv2.DIST_L2, 5)
imshow(dist, axes[0,1])
axes[0, 1].set_title('Distance Transform')
```

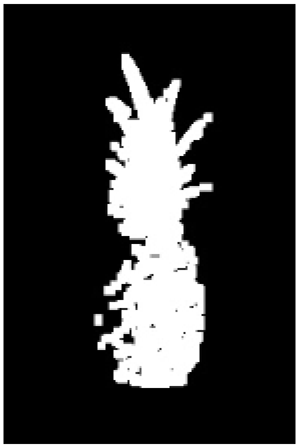
```
#foreground area
ret, sure_fg = cv2.threshold(dist, 0.5 * dist.max(), 255,
cv2.THRESH_BINARY)
sure_fg = sure_fg.astype(np.uint8)
imshow(sure_fg, axes[1,0])
axes[1, 0].set_title('Sure Foreground')

# unknown area
unknown = cv2.subtract(sure_bg, sure_fg)
imshow(unknown, axes[1,1])
axes[1, 1].set_title('Unknown')

plt.show()
```

Output:

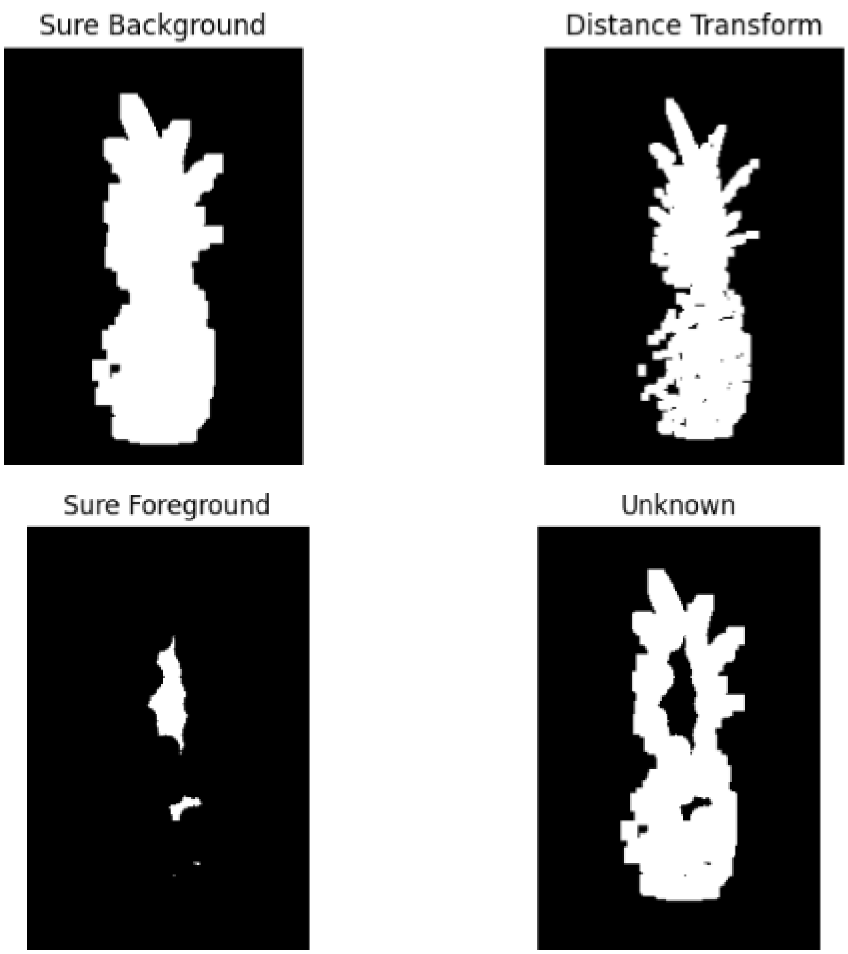
Threshold Image



noise removal



WARNING:matplotlib.image:Clipping input data to the valid range for imshow wit



Conclusion:

Certainly, let's delve into more detail about depth estimation in OpenCV:

1. Stereo Vision:

Pros:

- High Accuracy: Stereo vision relies on the triangulation principle, which can provide accurate depth maps when using a properly calibrated stereo camera setup.
- Real-time Capability: With appropriate hardware and optimizations, stereo vision can operate in real-time, making it suitable for applications like robotics and autonomous vehicles.

Cons:

- Calibration Requirement: Stereo vision necessitates precise calibration of the stereo camera system, which can be a time-consuming process.
- Sensitivity to Conditions: It can be sensitive to changes in lighting conditions and texture, affecting the quality of depth maps.